European Journal of Operational Research 237 (2014) 508–518

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Production, Manufacturing and Logistics

Strategic robust supply chain design based on the Pareto-optimal tradeoff between efficiency and risk

Edward Huang [a,*], Marc Goetschalckx [b]

[a] Department of Systems Engineering and Operations Research, George Mason University, Fairfax, VA 22030, USA
[b] H. Milton Stewart School of Industrial & Systems Engineering, Georgia Institute of Technology, 765 Ferst Drive, Atlanta, GA 30332, USA

ARTICLE INFO

Article history:
Received 8 December 2012
Accepted 15 February 2014
Available online 5 March 2014

Keywords:
Facilities planning and design
Supply chain network design
Stochastic programming
Branch and reduce algorithm

ABSTRACT

The strategic design of a robust supply chain has to determine the configuration of the supply chain so that its performance remains of a consistently high quality for all possible future conditions. The current modeling techniques often only consider either the efficiency or the risk of the supply chain. Instead, we define the strategic robust supply chain design as the set of all Pareto-optimal configurations considering simultaneously the efficiency and the risk, where the risk is measured by the standard deviation of the efficiency. We model the problem as the Mean–Standard Deviation Robust Design Problem (MSD-RDP). Since the standard deviation has a square root expression, which makes standard maximization algorithms based on mixed-integer linear programming non-applicable, we show the equivalency to the Mean–Variance Robust Design Problem (MV-RDP). The MV-RDP yields an infinite number of mixed-integer programming problems with quadratic objective (MIQO) when considering all possible tradeoff weights. In order to identify all Pareto-optimal configurations efficiently, we extend the branch-and-reduce algorithm by applying optimality cuts and upper bounds to eliminate parts of the infeasible region and the non-Pareto-optimal region. We show that all Pareto-optimal configurations can be found within a prescribed optimality tolerance with a finite number of iterations of solving the MIQO. Numerical experience for a metallurgical case is reported.

1. Introduction

For any corporation involved in delivering goods to their customers and operating in a competitive environment, the design of an efficient supply chain is of critical importance. *A supply chain is defined as a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer* (Mentzer et al., 2001). A supply chain encompasses the acquisition of raw material from suppliers, the transformation of materials into intermediate and finished products, the storage of materials or products, and the distribution of the finished products to customers.

The planning decisions with respect to a supply chain range from short-term decisions, such as vehicle dispatching and routing, to long-term decisions such as the definition of the corporate mission. Depending on their permanence, the decisions are typically divided into strategic, tactical, and operational planning. The goal of the strategic planning is to determine the configuration of the supply chain so that its long-term performance over the planning horizon is maximized. Given the permanence of the configuration decisions, the future conditions during the planning horizon cannot be known with certainty. Configuring a supply chain that will perform efficiently in a variety of unknown future environments belongs to the class of decision problems known as strategic planning under uncertainty. The supply chain configuration itself is called a robust design. The uncertainty of the future is usually modeled using scenarios (Peterson, Graeme, & Stephen, 2003). In the strategic design of supply chains there may be many thousands of parameters whose value is not known with certainty at the decision time. Even if the probability distributions of the individual parameters were known, constructing a joint probability distribution function for the scenarios in function of the parameters is not possible. In the following approach we model the uncertainty of the future by means of scenarios whose probabilities are assumed to be known. Scenarios may be grouped in classes or sets, such as best-guess, best case, and worst case scenarios, or represent high-impact, low-probability events. A robust (supply chain) design is the configuration that will perform efficiently for all these scenarios.

* Corresponding author. Tel.: +1 703 993 1672; fax: +1 703 993 1521.
E-mail addresses: chuang10@gmu.edu (E. Huang), marc.goetschalckx@isye.gatech.edu (M. Goetschalckx).

http://dx.doi.org/10.1016/j.ejor.2014.02.038
0377-2217/

Multiple definitions of robust design exist in the literature. In the area of strategic planning under uncertainty, related notions such as agility, adaptability, responsiveness, resilience, and flexibility also have been used. A recent survey of strategic supply chain planning and robust design is given in Klibi, Martel, and Guitouni (2010). One distinction they make with respect to robust design is between model, algorithm, and solution robustness. A design is defined as "model robust" if this design is "almost" feasible when the input data varies (Aghezzaf, 2005; Leung & Wu, 2004; Mulvey, Vanderbei, & Zenios, 1995; Yu & Li, 2000). A design is called "algorithm robust" if the algorithm performance is not affected by the presence of noise in the data. Sorensen (2004) developed an approximation of the number of evaluations in local search algorithms that is needed to find a candidate solution and considered the increased number of evaluations required by the presence of noise in the data. A design is called solution robust if the solution values remain "close" to each other when the input data changes (Aghezzaf, 2005; Leung & Wu, 2004; Mulvey et al., 1995; Yu & Li, 2000). Solution robustness is the focus of this research. Solution configuration robustness requires that the same (robust) supply chain configuration is used in the different scenarios and measures the variability of the objective function value (profit) over the different scenarios.

A second distinction in the robust design area is the modeling technique. One of the modeling techniques commonly used is stochastic programming. In stochastic programming models the uncertainty is assumed to be known and often modeled as a set of scenarios with known probabilities. The strategic supply chain design often uses a two-stage model, where the first stage decides the supply chain configuration and the second stage treats material flows and inventories as recourse variables after the uncertainty has been resolved. The objective is to maximize the expected value of the profit of all scenarios, i.e., the goal is to find an average or "median" type of solution. Ahmed and Sahinidis (2003) solve a stochastic capacity expansion problem with a given set of scenarios. Santoso, Ahmed, Goetschalckx, and Shapiro (2005) propose the use of a random sampling strategy, the sample average approximation scheme, to solve large-scale stochastic supply chain design problems. These approaches focus on the solution configuration and its expected efficiency and do not explicitly consider the robustness of the solution value, which may vary widely between the different scenarios.

A second modeling technique used for robust design is the fuzzy or possibilistic linear programming approach. When some parameters cannot be estimated deterministically, fuzzy logic can be a tool to model the uncertainty. Kabak and Ülengin (2011) propose a possibilistic linear programming model to optimize the strategic planning decisions where the uncertainty of the demand forecasts, yield rates, cost and capacities are modeled as fuzzy parameters. Pishvaee and Torabi (2010) propose a multi-objective possibilistic programming model for the closed-loop supply chain network design under uncertainty. Two objectives, the minimization of the total cost and the total tardiness, are considered in their work. Pishvaee, Razmi, and Torabi (2012) consider social responsibility in the supply chain network design problem and propose a robust possibilistic programming to optimize the configuration of supply chain network with respect to both social and economic aspects.

A third modeling technique used for robust design is the robust optimization approach. This approach assumes that the probabilities of the scenarios are not available and the objective is to either minimize the maximum cost or to maximize the minimum profit over all possible scenarios (Atamtürk & Zhang, 2007). If a particularly bad scenario is possible, even though it has a very low probability of occurrence, then this scenario may determine the supply chain configuration. The goal of this approach is to find a "center" type of solution.

A fourth approach assumes that the probabilities of scenarios are known and considers the tradeoff between expected value, solution robustness, and other measures such as environmental factors (Amin & Zhang, 2013; Tang, Zhang, & Xu, 2013; Wang, Lai, & Shi, 2011), flow time or lost sale (Liu & Papageorgiou, 2013). The solution robustness is evaluated either based on its variance (Markowitz, 1991; Mulvey et al., 1995) or absolute deviation (Leung & Wu, 2004; Yu & Li, 2000). These models consider the portfolio selection in which the decision variables are continuous. Recently, different measurements of the solution robustness are proposed for the strategic supply chain design problems including the variance (Azaron, Brown, Tarim, & Modarres, 2008; Azaron, Furmans, & Modarres, 2008; Azaron et al., 2010; You, Wassick, & Grossmann, 2009), the financial risk (Azaron, Brown et al., 2008; Azaron, Furmans et al., 2008; Guillén, Mele, Bagajewics, Espuña, & Puigjaner, 2005; You et al., 2009), the variance index (You et al., 2009), and the downside risk (Azaron, Brown et al., 2008; Azaron, Furmans et al., 2008; Azaron et al., 2010; You et al., 2009). Several solution techniques, which improve the solution time of identifying a robust supply chain design for a given tradeoff weight between the efficiency and the solution robustness, are developed. However, identifying all Pareto-optimal configurations efficiently is still a challenging problem since there are an infinite number of possible tradeoff weights between the efficiency and the solution robustness.

In the following we consider solution configuration robustness. In other words, the supply chain configuration has to be chosen before any scenario is realized and the solution robustness is defined as the variability of the solution value between the scenarios. Specifically, the objective is to find all Pareto-optimal configurations with respect to the expected value and standard deviation of the scenario profits. The use of the standard deviation of the scenario profits instead of the variance allows a more intuitive interpretation and comparison between configurations and a direct relationship between the coefficient of variation of the solution value and the objective function. The coefficient of variation is dimensionless which allows for the specification of a dimensionless allowable tolerance gap and also avoids dependencies on the currency units of the profit or cost.

If all Pareto-optimal configurations can be identified, we can plot these configurations in a risk analysis graph with the expected value on the horizontal axis and the standard deviation on the vertical axis so decision makers can choose the configuration based on their preferences. Fig. 1 shows a motivational example of a mean–standard deviation risk analysis graph for a tutorial supply chain network design problem. Three Pareto-optimal configurations exist in this example. Compared to other existing approaches, the stochastic programming approach will find the configuration with maximum expected profit value and maximum standard deviation, which is generated by the configuration ("010011"). If the decision maker is risk-seeking, this configuration will be selected. The robust optimization approach using the max–min profit objective will select the configuration with minimum standard deviation which is the configuration ("110110"). If the decision maker is extremely risk-averse then this configuration will be selected. Neither approach will identify the configuration ("011011") even though it is also Pareto-optimal. In this research, we will develop an efficient methodology to identify all Pareto-optimal configurations and to compute the range of the coefficient of variation for which each of them is dominant. A particular configuration may be dominant for a large fraction of the range of the coefficient of variation, but it may be different from the configurations found by stochastic optimization and robust optimization. The final selection of the supply chain configuration to be implemented can then be based on the risk tradeoff of the decision maker and on other